Online Appendix

ESG and the Stock Market: Is ESG Exposure Systematic?

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A1. Detailed description of individual ESG measures

We consider 38 market-level individual ESG measures including:

(1) 14 environmental predictors

- E1: Formal Environmental Policy
- E2: Environmental Management System
- E3: External Certification of EMS
- E4: Environmental Fines and Non-monetary Sanctions
- E5: Participation in Carbon Disclosure Project
- E6: Scope of Corporate Reporting on GHG Emissions
- E7: Programs and Targets to Increase Renewable Energy Use
- E8: Carbon Intensity
- E9: Carbon Intensity Trend
- E10: % Primary Energy Use from Renewables
- E11: Operations Related Controversies or Incidents
- E12: Formal Policy or Program on Green Procurement
- E13: Environmental Supply Chain Incidents
- E14: Products & Services Related Controversies or Incidents

(2) 11 social predictors

- S1: Policy on Freedom of Association
- S2: Formal Policy on the Elimination of Discrimination
- S3: Programs to Increase Workforce Diversity
- S4: Percentage of Employees Covered by Collective Bargaining Agreements
- S5: Employee Turnover Rate
- S6: Employee Related Controversies or Incidents
- S7: Scope of Social Supply Chain Standards
- S8: Supply Chain Monitoring System
- S9: Social Supply Chain Incidents
- S10: Customer Related Controversies or Incidents
- S11: Society & Community Related Controversies or Incidents

(3) 13 governance predictors

- G1: Policy on Bribery and Corruption
- G2: Whistleblower Programs
- G3: Signatory to UN Global Compact
- G4: Tax Transparency
- G5: Business Ethics Related Controversies or Incidents
- G6: CSR Reporting Quality
- G7: External Verification of CSR Reporting
- G8: Oversight of ESG Issues
- G9: Executive Compensation Tied to ESG Performance
- G10: Governance Related Controversies or Incidents
- G11: Policy on Political Involvement and Contributions
- G12: Total Value of Political Contributions or Political Spending
- G13: Public Policy Related Controversies or Incidents

A2. Correlations of individual ESG measures

Table A2: Pairwise correlations of individual ESG measures
This table reports the pairwise correlations of individual ESG measures in Online Appendix A1. The sample spans the period from Aug 2009 to Sep 2019.

corr	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12	E13	E14	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11	G12	G13
E1	1.00																																					
E2	0.52	1.00																																				
E3	0.26	-0.25	1.00																																			
E4	-0.08	-0.83	0.49	1.00																																		
E5	0.14	-0.08	0.20	0.24	1.00																																	
E6	0.12	-0.29	0.47	0.47	0.43	1.00																																
E7	0.10	-0.66	0.51	0.87	0.22	0.45	1.00																															
E8	0.19	-0.40	0.12	0.47	0.08	0.30	0.47	1.00																														
E9	0.00	-0.46	0.13	0.48	0.14	0.43	0.44	0.77	1.00																													
E10	0.37	-0.22	0.18	0.30	-0.01	0.10	0.30	0.59	0.39	1.00																												
E11	0.48	0.95	-0.33	-0.74	-0.06	-0.30	-0.62	-0.33	-0.38	-0.23	1.00																											
E12	0.34	0.41	0.08	-0.33	0.01	-0.06	-0.12	-0.14	-0.16	0.07	0.18	1.00																										
E13	-0.33	-0.93	0.44	0.89	0.17	0.38	0.73	0.41	0.46	0.27	-0.89	-0.35	1.00																									
E14	0.49	0.47	0.06	-0.20	0.15	-0.06	-0.22	-0.07	-0.03	0.06	0.59	-0.18	-0.25	1.00																								
S1	0.12	-0.29	0.32	0.46	0.17	0.37	0.58	0.11	0.14	-0.06	-0.36	0.16	0.36	-0.27	1.00																							
S2	0.56	0.27	0.12	0.21	0.09	0.13	0.26	0.16	0.09	0.10	0.40	-0.04	-0.07	0.50	0.34	1.00																						
S3	0.01	-0.26	0.23	0.30	0.03	0.19	0.40	0.19	0.21	0.07	-0.41	0.40	0.31	-0.40	0.68	0.11	1.00																					
S4	0.26	0.02	0.04	0.16	0.04	0.18	0.30	0.06	0.05	0.01	-0.06	0.20	0.07	-0.07	0.76	0.46	0.71	1.00																				
S5	0.35	-0.06	-0.14	0.08	0.00	0.02	0.05	0.52	0.34	0.89	-0.06	0.04	0.07	0.13	-0.09	0.10	0.02	0.12	1.00																			
S6	0.49	0.91	-0.31	-0.67	-0.10	-0.28	-0.57	-0.29	-0.33	-0.20	0.99	0.15	-0.84	0.62	-0.36	0.48	-0.42	-0.07	-0.05	1.00																		
S7	0.01	-0.18	0.17	0.17	-0.04	0.17	0.26	0.04	0.07	0.09	-0.38	0.46	0.23	-0.38	0.65	0.04	0.87	0.75	0.12	-0.41	1.00																	
S8	0.20	0.68	-0.06	-0.74	-0.14	-0.17	-0.49	-0.47	-0.44	-0.32	0.49	0.60	-0.71	-0.02	-0.25	-0.34	-0.08	-0.13	-0.28	0.42	0.03	1.00																
S9	0.14	-0.14	0.24	0.40	0.15	0.07	0.28	0.11	0.08	0.05	0.04	-0.32	0.32	0.44	-0.06	0.45	-0.25	-0.19	-0.12	0.13	-0.34	-0.43	1.00															
S10	0.56	0.81	-0.18	-0.51	-0.06	-0.18	-0.40	-0.18	-0.23	-0.13	0.90	0.09	-0.67	0.72	-0.19	0.63	-0.30	0.10	-0.01	0.92	-0.29	0.27	0.15	1.00														
S11	0.49	0.88	-0.26	-0.65	-0.09	-0.26	-0.55	-0.27	-0.32	-0.17	0.96	0.10	-0.79	0.68	-0.34	0.48	-0.44	-0.07	-0.04	0.97	-0.41	0.38	0.14	0.94	1.00													
G1	0.46	-0.05	0.35	0.49	0.11	0.25	0.46	0.31	0.22	0.20	0.07	-0.17	0.31	0.46	0.31	0.83	0.17	0.38	0.07	0.15	0.07	-0.49	0.58	0.37	0.19	1.00												
G2	0.54	0.45	-0.19	-0.32	0.00	-0.08	-0.26	0.09	-0.06	0.48	0.37	0.28	-0.39	0.25	0.13	0.33	0.13	0.44	0.69	0.34	0.27	0.04	-0.29	0.36	0.32	0.06	1.00											
G3	-0.24	-0.45	0.21	0.37	-0.03	0.20	0.42	0.08	0.06	0.00	-0.57	0.08	0.46	-0.47	0.71	-0.03	0.72	0.63	-0.02	-0.59	0.76	-0.22	-0.25	-0.46	-0.57	0.05	0.04	1.00										
G4	0.42	0.43	-0.01	-0.36	0.06	-0.01	-0.33	-0.06	-0.11	0.21	0.30	0.42	-0.34	0.18	-0.01	0.10	0.16	0.25	0.30	0.27	0.23	0.27	-0.17	0.23	0.21	-0.03	0.65	-0.13	1.00									
G5	0.44	0.93	-0.38	-0.76	-0.13	-0.31	-0.64	-0.32	-0.36	-0.21	0.97	0.20	-0.88	0.55	-0.27	0.43	-0.30	0.08	0.00	0.95	-0.23	0.45	-0.09	0.92	0.94	0.08	0.46	-0.44	0.31	1.00								
G6	0.37	0.31	0.25	-0.17	-0.04	0.16	0.10	-0.10	-0.09	-0.02	0.13	0.59	-0.28	-0.16	0.39	0.06	0.49	0.49	-0.07	0.09	0.49	0.52	-0.43	0.13	0.08	-0.03	0.21	0.21	0.23	0.18	1.00							
G7	0.24	0.82	-0.34	-0.88	-0.13	-0.38	-0.68	-0.38	-0.40	-0.24	0.72	0.42	-0.86	0.17	-0.28	-0.11	-0.18	-0.06	-0.10	0.65	-0.11	0.71	-0.39	0.51	0.63	-0.36	0.34	-0.32	0.33	0.72	0.38	1.00						
G8	0.40	0.15	0.39	0.07	0.11	0.21	0.20	0.01	-0.05	0.07	-0.04	0.58	0.00	-0.07	0.36	0.18	0.50	0.41	-0.03	-0.04	0.53	0.29	-0.08	0.01	-0.09	0.17	0.22	0.28	0.51	-0.04	0.39	-0.02	1.00					
G9	0.27	0.09	0.24	0.04	0.06	0.11	0.05	0.04	-0.02	0.02	-0.06	0.43	0.05	-0.02	0.26	0.14	0.45	0.33	-0.02	-0.07	0.47	0.14	-0.02	-0.05	-0.17	0.17	0.23	0.20	0.63	-0.05	0.22	-0.06	0.72	1.00				
G10	0.47	0.96	-0.36	-0.79	-0.11	-0.32	-0.65	-0.34	-0.38	-0.22	0.99	0.23	-0.92	0.55	-0.36	0.35	-0.38	-0.04	-0.05	0.98	-0.33	0.54	-0.03	0.89	0.95	0.01	0.38	-0.55	0.32	0.98	0.18	0.76	-0.03	-0.06	1.00			
G11	0.14	-0.38	0.26	0.56	0.15	0.33	0.69	0.30	0.26	0.13	-0.39	0.04	0.46	-0.17	0.55	0.22	0.54	0.52	-0.04	-0.36	0.35	-0.26	0.15	-0.21	-0.35	0.44	-0.14	0.36	-0.08	-0.39	0.26	-0.40	0.28	0.18	-0.39	1.00		
G12	-0.09	-0.64	0.01	0.70	0.18	0.30	0.66	0.43	0.49	0.28	-0.48	-0.53	0.60	-0.08	0.33	0.19	0.01	0.16	0.25	-0.44	-0.07	-0.72	0.21	-0.30	-0.41	0.28	-0.10	0.19	-0.37	-0.46	-0.25	-0.62	-0.31	-0.26	-0.50	0.44	1.00	
G13	-0.11	-0.77	0.45	0.91	0.20	0.35	0.76	0.43	0.39	0.27	-0.65	-0.40	0.86	-0.09	0.30	0.23	0.14	0.00	0.03	-0.56	0.01	-0.75	0.65	-0.47	-0.54	0.52	-0.37	0.25	-0.35	-0.71	-0.37	-0.85	0.01	0.03	-0.71	0.46	0.60	1.00

A3. Time series of market-level ESG subindices

Figure A3.1: Time series of market-level ESG subindex in the environmental category

This figure plots the time series of the market-level ESG subindex in the environmental category, The subindex aggregates individual ESG predictors in the environmental category and is standardized.

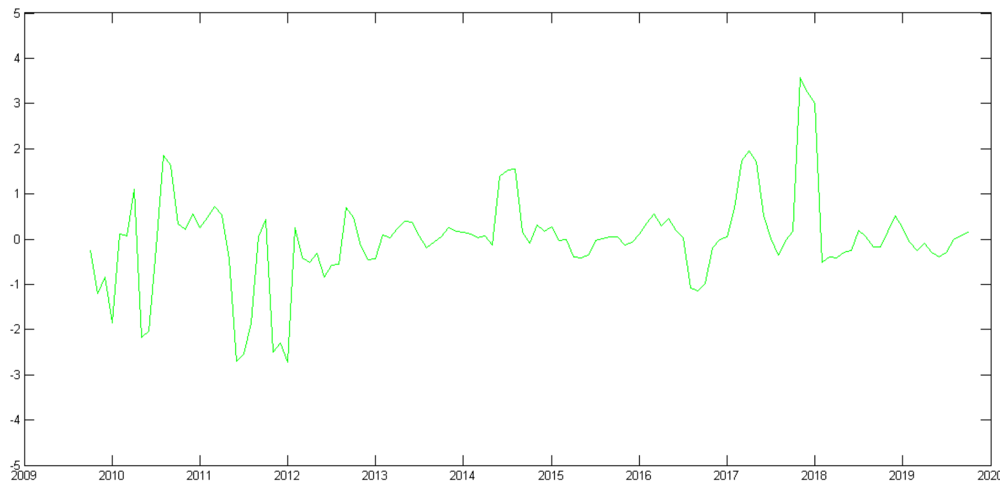


Figure A3.2: Time series of market-level ESG subindex in the social category

This figure plots the time series of the market-level ESG subindex in the social category. The subindex aggregates individual ESG predictors in the social category and is standardized.

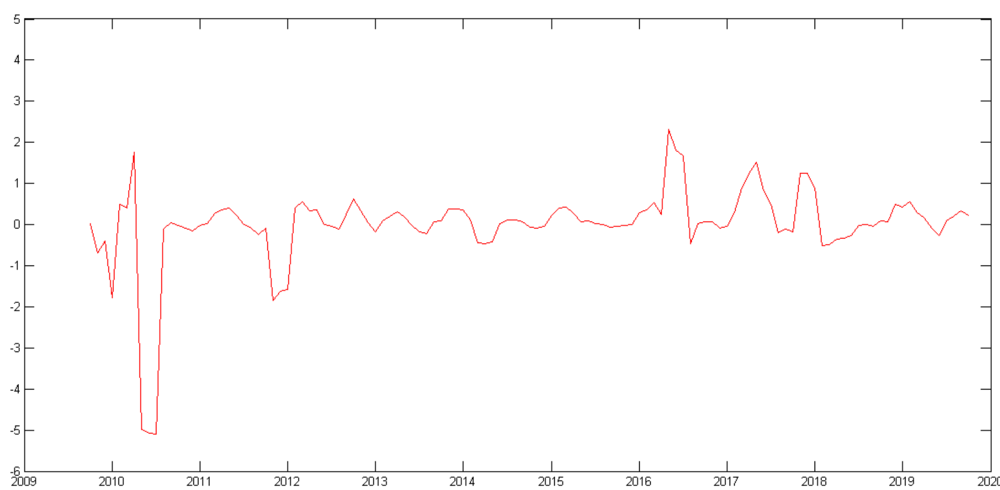
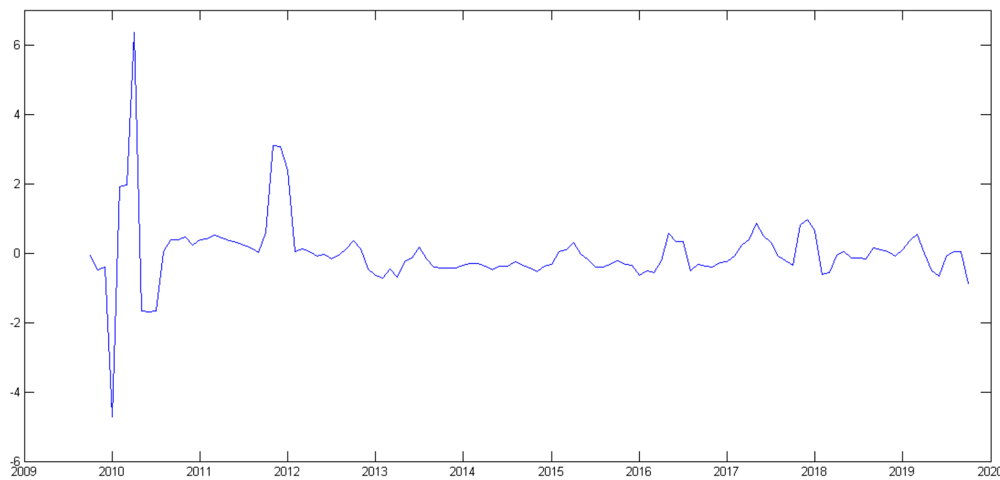


Figure A3.3: Time series of market-level ESG subindex in the governance category

This figure plots the time series of the market-level ESG subindex in the governance category. The subindex aggregates individual ESG predictors in the governance category and is standardized.



A4. Alternative specifications of detrending

Table A4: Predicting market return with composite ESG index under alternative detrending methods

This table reports the regressions of future market return on composite ESG index after removing the time trend. Composite ESG index is constructed by aggregating information from individual ESG predictors based on the *PLS* method and covers all three ESG categories. The detrending methods we consider include a linear time trend in specification (1), a quadratic time trend in specification (2), a cubic time trend in specification (3), and a stochastic trend in specification (4) based on a five-year window, which is computed as the deviation in the ESG index for month t from a 60-month moving average from month $t-59$ to month t. Newey-West t-values are reported below the coefficients.

	(1)	(2)	(3)	(4)
linear	0.95			
	(6.10)			
quadratic		0.94		
		(6.10)		
cubic			0.95	
			(6.16)	
stochastic				0.70
				(3.62)
$R^2(\%)$	6.91	6.83	6.87	4.20

A5. Comparison among ESG indices and the subindices

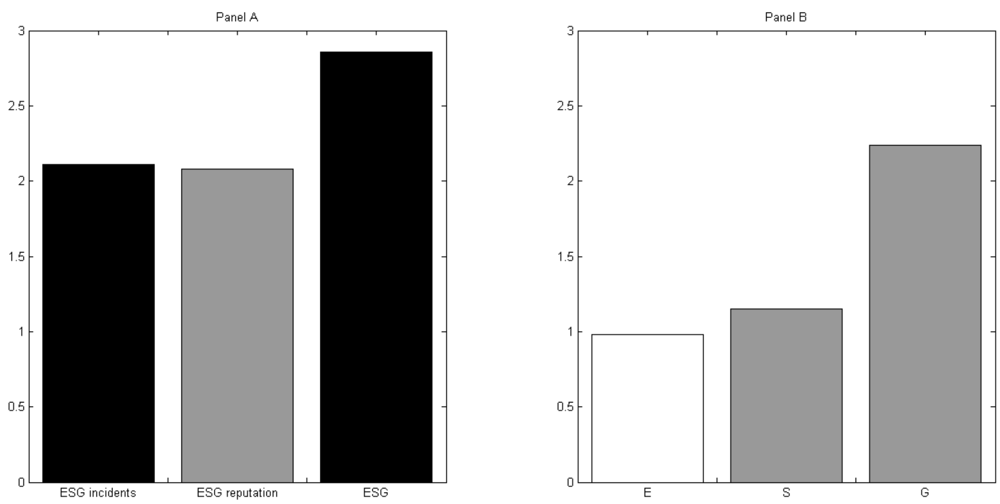
In this subsection, we evaluate and compare the out-of-sample predictive performance of market-level ESG indices and the subindices. To evaluate the out-of-sample performance, we use the R^2_{OS} of Campbell and Thompson (2008) and the MSFE-adjusted statistic test of Clark and West (2007). R^2_{OS} measures the proportional reduction in the mean squared forecast error (MSFE) for the predictive regression forecast vis-*á*-vis the benchmark forecast. To uncover whether the predictive regression forecast produces a statistically significant improvement in MSFE, we use Clark and West (2007)'s MSFE-adjusted statistic to test the null hypothesis that the historical average MSFE is not more than that of the predictive regression forecast against the alternative hypothesis that the historical average MSFE is greater than that of the predictive regression forecast, corresponding to $H_0 : R^2_{OS} \leq 0$ against $H_A : R^2_{OS} > 0$.

In the baseline implementation, we use the first half of the full sample as the initial training period and the rest as the out-of-sample forecast evaluation period. Importantly, we formulate the recursively estimated month t market-level ESG indices using the available data observed no later than the current month t to predict the following month $t+1$ return out-of-sample, thereby eliminating any look-ahead bias. In addition, when constructing the composite ESG index with limited out-of-sample size, we consider the averaging of the coefficient estimates over previous periods, as suggested by Light et al. (2017). The parameters can be estimated more precisely by averaging over previous periods than only relying on the most recent one because smoothing over time helps stabilize the coefficient estimates and, consequently, improving return forecasts and reducing the risk of overfitting.

Overall, it is shown that the composite ESG index, which captures sustainable growth information from the environmental, social, and governance categories, exhibits stronger predictive performance than the subindices capturing information from only one of the three categories, and market-level indices based on alternative ESG databases consistently display similar predictability out-of-sample.

Figure A5: Out-of-sample performance of market-level ESG indices and the subindices

Panel A of this figure plots the out-of-sample $R^2_{OS}(\%)$ of market-level ESG indices constructed based on alternative ESG information, including abnormal change of aggregate news mentions of risk incidents related to ESG events and monthly change in aggregate ESG reputation risk at market level, respectively, as well as the composite ESG index constructed by aggregating information from individual ESG measures using the *PLS* approach, which covers all three ESG categories. Panel B of this figure plots the out-of-sample $R^2_{OS}(\%)$ of the market-level ESG subindex in the environmental, social, and governance categories, respectively. Statistical significance for R^2_{OS} is based on the p-value of Clark and West (2007) MSFE-adjusted statistic for testing H_0: $R^2_{OS} \leq 0$ against H_A: $R^2_{OS} > 0$. Bars colored in black, grey, and white indicate significance at 5% and 10% levels, and insignificance, respectively.



A6. Alternative aggregations

Table A6.1: Predicting market return with equal- and volatility-weighted ESG indices

Panel A and Panel B report the regression slope, Newey-West t-value, and monthly $R^2(\%)$ of predicting future market return with alternative market-level ESG indices as $R_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1}$, where R_{t+1} is market excess return in month $t+1$, and predictor X_t in Panel A (B) represents alternative market-level ESG index constructed by aggregating information from individual ESG measures using simple averaging (volatility weighting) method. In each panel, predictor X_t represents market-level ESG index which covers all three ESG categories and the subindices in the environmental, social, and governance categories, respectively. The t-values are reported below the coefficients.

	(1)	(2)	(3)	(4)
		Panel A: Equ		
ESG	0.53			
	(3.51)			
E		0.45		
		(2.12)		
S			0.42	
			(4.85)	
G				0.41
				(2.97)
$R^2(\%)$	2.19	1.52	1.33	1.26
		Panel B: Vol		
ESG	0.54			
	(3.52)			
E		0.45		
		(2.13)		
S			0.42	
			(4.86)	
G				0.41
				(3.00)
$R^2(\%)$	2.20	1.54	1.33	1.28

Table A6.2: Predicting market return with market-level ESG indices conducted based on market equity weights

Panel A and Panel B report the regression slope, Newey-West t-value, and monthly $R^2(\%)$ of predicting future market return with market-level ESG indices as $R_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1}$, where R_{t+1} is market excess return in month $t+1$. Predictor X_t in Panel A (B) represents market-level composite ESG index (alternative market-level ESG index) constructed by aggregating information from individual ESG measures using the *PLS* approach (simple averaging method), which covers all three ESG categories and the subindices in the environmental, social, and governance categories, respectively. Individual ESG measures in both Panel A and Panel B are conducted by aggregating firm-level ESG subcategory indicators with market equity weights. The t-values are reported below the coefficients.

	(1)	(2)	(3)	(4)
		Panel A		
ESG	0.89			
	(6.06)			
E		0.62		
		(3.09)		
S			0.64	
			(2.47)	
G				0.68
				(3.67)
$R^2(\%)$	6.08	2.98	3.12	3.59
		Panel B		
ESG	0.51			
	(2.86)			
E		0.29		
		(1.31)		
S			0.39	
			(4.11)	
G				0.60
				(2.84)
$R^2(\%)$	2.20	0.65	1.16	2.72

A7. Long horizons

Table A7: ESG and long horizon predictability

Panel A (B) reports the regression slope, Newey-West t-value, and $R^2(\%)$ of predicting future cumulative market return over one-year (three-year) horizon with composite ESG index as $R_{t+h} = \alpha + \beta X_t + \varepsilon_{t+h}$. R_{t+h} is the cumulative market excess return between month t and month t+h, where $h = 12$ ($h = 36$) in Panel A (B). Predictor X_t in each panel represents the composite ESG index which covers all three ESG categories and the subindices in the environmental, social, and governance categories, respectively. In each panel, we construct the composite ESG index by aggregating information from individual ESG predictors using the *PLS* approach. The t-values are reported below the coefficients.

	(1)	(2)	(3)	(4)
		Panel A: 1Y		
ESG	2.72			
	(3.21)			
E		1.57		
		(1.58)		
S			2.75	
			(3.51)	
G				3.06
				(4.24)
$R^2(\%)$	11.97	4.00	12.21	15.11
		Panel B: 3Y		
ESG	4.08			
	(4.89)			
E		4.35		
		(5.12)		
S			3.56	
			(3.37)	
G				3.56
				(6.64)
$R^2(\%)$	18.07	20.55	13.80	13.75

A8. Model complexity

In this subsection, we analyze the predictability by using the model complexity approach, which requires only 36 months of data for training and provide eight out of 11 years for out-of-sample evaluation. Table A8 reports the out-of-sample results. Similar to Kelly et al. (2024), despite of negative R^2_{OS}, there is still economic value of predictability to investors who time the market.

First, based on a low level of shrinkage with ridge parameter $z = 0.1$, we observe that the monthly out-of-sample R^2_{OS} is large and negative at -238.65%. Despite the large and negative R^2_{OS}, we find that a market timer can still generate positive economic profits, with an annualized Sharpe ratio of 0.54. When we increase the ridge parameter by 100 times, the out-of-sample R^2_{OS} rises to -23.88% per month. With this much shrinkage, the benefits of market timing are economically sizable: the timing Sharpe ratio improves from 0.54 to roughly 0.80 per annum. When $z = 10^2$, the monthly out-of-sample R^2_{OS} in the heavily regularized regression remains negative with a smaller magnitude of -4.87%, and the annualized out-of-sample Sharpe ratio of the strategy is 0.85. Higher ridge shrinkage earns further profits. When $z = 10^3$, the monthly out-of-sample R^2_{OS} becomes much less negative and closer to zero, and the annualized out-of-sample Sharpe ratio reaches nearly 0.94.

Next, we examine whether employing machine learning models with a higher degree of complexity can yield further benefits. The machine learning strategy uses the same ESG information set as in the kitchen sink strategy while it just exploits the ESG information in a high-dimensional nonlinear approach. The last column of Table A8 shows that the machine learning timing strategy with a high level of model complexity further enhances out-of-sample performance: the average monthly out-of-sample R^2_{OS} becomes positive, and the market timing Sharpe ratio arrives at approximately 0.99 per annum. Overall, these results indicate that appropriate regularization and model flexibility substantially strengthen the out-of-sample predictability of ESG-based signals.

Table A8: ESG predictability via model complexity

This table shows the out-of-sample $R^2_{OS}(\%)$ and the market timing strategy performance in terms of Sharpe ratio based on ESG information with varying degrees of ridge shrinkage, and machine learning model with a high level of model complexity, respectively. Sharpe ratio is the annualized average market timing portfolio excess return divided by its standard deviation.

	Kitchen Sink				High Complexity
	$z = 0.1$	$z = 10$	$z = 10^2$	$z = 10^3$	$P = 12000$
$R^2_{OS}(\%)$	-238.65	-23.88	-4.87	-0.42	0.37
Sharpe ratio	0.54	0.80	0.85	0.94	0.99

A9. Detailed description of economic variables

In the robustness check, we control for the following 14 economic variables of Goyal and Welch (2008).

- Dividend-price ratio (log), DP: log of a 12-month moving sum of dividends paid on the S&P 500 index minus the log of stock prices (S&P 500 index).
- Dividend yield (log), DY: log of a 12-month moving sum of dividends minus the log of lagged stock prices.
- Earnings-price ratio (log), EP: log of a 12-month moving sum of earnings on the S&P 500 index minus the log of stock prices.
- Dividend-payout ratio (log), DE: log of a 12-month moving sum of dividends minus the log of a 12-month moving sum of earnings.
- Stock return variance, $SVAR$: sum of squared daily returns on the S&P 500 index.
- Book-to-market ratio, BM: ratio of book value to market value for the Dow Jones Industrial Average.
- Net equity expansion, $NTIS$: ratio of a 12-month moving sum of net equity issues by NYSE-listed stocks to the total end-of-year market capitalization of NYSE stocks.
- Treasury bill rate, TBL: interest rate on a 3-month Treasury bill (secondary market).
- Long-term yield, LTY: long-term government bond yield.
- Long-term return, LTR: return on long-term government bonds.
- Term spread, TMS: long-term yield minus the Treasury bill rate.
- Default yield spread, DFY: difference between BAA- and AAA-rated corporate bond yields.
- Default return spread, DFR: long-term corporate bond return minus the long-term government bond return.
- Inflation, $INFL$: calculated from the consumer price inflation (CPI) for all urban consumers; we use lagged 2-month inflation in the regression to account for the delay in CPI releases.

A10. Industry portfolios

Table A10: Forecasting industry portfolio returns

Panel A (B) reports the regression slope, Newey-West t-value, and in-sample $R^2(\%)$ of predicting future industry returns with ESG subindices as $R^i_{t+1} = \alpha^i + \beta^i X^i_t + \varepsilon_{t+1}$, where R^i_{t+1} is monthly excess return of industry i in month t+1, predictor X^i_t denotes the ESG subindices in the environmental, social, and governance categories, respectively.

Industry	β^i	t-value	$R^2(\%)$	Industry	β^i	t-value	$R^2(\%)$
			Panel A: Environmental				
NoDur	0.59	3.15	3.37	Telcm	0.83	2.49	4.48
Durbl	1.14	1.98	3.36	Utils	0.30	0.83	0.89
Manuf	1.08	3.14	4.76	Shops	1.10	3.30	8.63
Enrgy	0.97	2.14	2.72	Hlth	0.69	2.47	3.16
Chems	0.58	2.25	2.55	Money	0.81	2.44	2.83
BusEq	0.95	2.80	4.48	Other	0.92	2.58	4.59
			Panel B: Social				
NoDur	0.30	1.62	0.85	Telcm	0.46	1.78	1.36
Durbl	0.48	1.31	0.61	Utils	0.30	1.29	0.87
Manuf	0.61	1.93	1.54	Shops	0.81	3.54	4.71
Enrgy	0.46	1.17	0.61	Hlth	0.50	2.85	1.68
Chems	0.29	1.36	0.65	Money	0.64	2.06	1.74
BusEq	0.76	2.94	2.88	Other	0.56	1.74	1.70
			Panel C: Governance				
NoDur	0.36	2.60	1.27	Telcm	0.86	3.90	4.86
Durbl	0.84	2.44	1.82	Utils	0.33	1.77	1.11
Manuf	0.98	5.55	3.95	Shops	0.78	4.52	4.30
Enrgy	0.98	4.08	2.78	Hlth	0.29	1.21	0.57
Chems	0.48	4.38	1.71	Money	0.53	2.81	1.20
BusEq	0.87	3.24	3.76	Other	0.81	3.88	3.52

A11. ESG portfolios and market return

Table A11: Forecasting market return with composite ESG portfolio index

Panel A reports the regression slope, Newey-West t-value, in-sample $R^2(\%)$, and out-of-sample $R^2_{OS}(\%)$ of predicting future market return with composite ESG portfolio index as $R_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1}$, where R_{t+1} is market excess return in month t+1, predictor X_t represents the composite ESG portfolio index which covers all three ESG categories. The *PLS* approach is employed to extract predictive signal in long-short ESG portfolio returns as the composite ESG portfolio index. The ESG portfolios are constructed based on stocks' exposures to individual ESG predictors. Statistical significance for R^2_{OS} is based on the p-value of Clark and West (2007) MSFE-adjusted statistic for testing H_0: $R^2_{OS} \leq 0$ against H_A: $R^2_{OS} > 0$. $***$, $**$, and $*$ indicate significance at 1%, 5%, 10% levels, respectively. Panel B reports the regression slope, Newey-West t-value, and $R^2(\%)$ of predicting composite ESG portfolio index with composite ESG index. The composite ESG index is constructed by aggregating information from individual ESG predictors.

β	t-value	$R^2(\%)$	$R^2_{OS}(\%)$
Panel A: composite ESG portfolio index and market return			
1.36	3.56	18.30	3.27**
Panel B: composite ESG index and ESG portfolio index			
0.14	3.03	1.99	–

A12. Alternative ESG data with annual frequency till the latest sample

Table A12: Forecasting market return using ESG measures with annual frequency

This table reports the regression slope, Newey-West t-value, in-sample $R^2(\%)$, and out-of-sample $R^2_{OS}(\%)$ of predicting future market return with alternative ESG information as $R_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1}$, where R_{t+1} represents future market excess return, and predictor X_t is constructed by aggregating information from individual ESG measures with annual frequency using the *PLS* approach. Statistical significance for R^2_{OS} is based on the p-value of Clark and West (2007) MSFE-adjusted statistic for testing H_0: $R^2_{OS} \leq 0$ against H_A: $R^2_{OS} > 0$. $***$, $**$, and $*$ indicate significance at 1%, 5%, 10% levels, respectively.

β	t-value	$R^2(\%)$	$R^2_{OS}(\%)$
0.51	1.88	1.33	0.86*

A13. Greenwashing contamination

Amid mounting pressure for companies to report on their environmental, social, and governance (ESG) performance, they tend to selectively disclose relatively harmless impacts while masking their true performance. This greenwashing can create a falsely positive impression of overall sustainability that can obscure the true link between ESG performance and stock returns. Kim and Lyon (2015) argue that growing firms are more likely to be exposed to pressures arising from the need to maintain their "license to operate", and given that a green image can help them build positive reputations and regulatory relationships, they have stronger incentives to engage in greenwashing. Hence, we hypothesize that growth (value) firms are more (less) likely to engage in greenwashing and classify the whole sample into subsamples according to the definition of growth versus value. Then we investigate the predictive relations between future market return and composite ESG index based on firms in subsamples separately. Furthermore, since companies with a higher proportion of independent directors are generally perceived to have better governance mechanisms and are less likely to engage in greenwashing, we also divide the entire sample into subgroups based on the percentage of independent directors.

Panel A of Table A13 shows that the predictability of ESG on market return is stronger for firms which have weaker incentives to engage in greenwashing, with higher (lower) predictive coefficient, t-value as well as $R^2(\%)$ among firms with lower (higher) greenwashing potential. Results based on ESG subindices show that the difference between firms with high and low greenwashing potentials is substantial in the environmental category: the R^2 among firms with low greenwashing potential reaches approximately 8% per month and is more than 2.7 times of the monthly R^2 among firms with high greenwashing potential, which is less than 3%. Similarly, in Panel B of Table A13, we observe higher (lower) predictive coefficient, t-value as well as $R^2(\%)$ among firms with higher (lower) share of independent directors and thus lower (higher) greenwashing potential.

Table A13: Predictive performance among firms with high and low greenwashing potentials
This table reports the predictive regressions of future market return with composite ESG index among firms with high and low greenwashing potentials, respectively. We consider growth (value) firms in Panel A and firms with low (high) share of independent directors in Panel B as firms which are more (less) likely to engage in greenwashing. In each of the two subsamples, we consider the composite ESG index which covers all three ESG categories and the subindices in the environmental, social, and governance categories, respectively. Newey-West t-values are reported.

low greenwashing			high greenwashing		
β	t-value	$R^2(\%)$	β	t-value	$R^2(\%)$
Panel A					
Environmental, Social and Governance					
1.12	5.41	9.62	1.00	4.37	7.65
Environmental					
1.02	4.05	8.04	0.61	2.64	2.89
Social					
0.82	2.58	5.10	0.78	3.40	4.70
Governance					
0.78	3.47	4.68	0.56	2.03	2.38
Panel B					
Environmental, Social and Governance					
1.03	6.62	8.15	0.86	4.83	5.60
Environmental					
0.84	2.89	5.43	0.80	2.64	4.85
Social					
0.56	2.02	2.40	0.64	2.99	3.14
Governance					
0.81	4.25	5.00	0.68	4.09	3.54

A14. Underreaction to market-level ESG information

Table A14.1: Predicting ESG flows with composite ESG index

This table report the regressions of future ESG flows on the market-level ESG index. "ESG flows" equals the quarter's dollar flow into ESG funds scaled by the average total CRSP market capitalization during the quarter that contains the given month. The market-level ESG index covers all three ESG categories and is constructed by aggregating information from individual ESG predictors based on the *PLS*, *Equ*, and *Vol* methods, respectively. Newey-West t-values are reported.

Pls			*Equ*			*Vol*		
β	t-value	$R^2(\%)$	β	t-value	$R^2(\%)$	β	t-value	$R^2(\%)$
-0.82	-0.05	0.00	4.96	0.27	0.04	4.86	0.26	0.04

Table A14.2: Forecasting market return with composite ESG index during periods with high and low aggregate ESG concerns

This table reports the predictive regressions of future market return with composite ESG index during periods with high and low aggregate ESG concerns, respectively. The market-level ESG index covers all three ESG categories and is constructed by aggregating information from individual ESG predictors based on the *PLS* approach. Aggregate ESG concerns are estimated based on aggregate mentioning of risk incidents related to ESG events. Periods with high and low aggregated ESG concerns are classified based on the median level. Newey-West t-values are reported.

high ESG concerns			low ESG concerns		
β	t-value	$R^2(\%)$	β	t-value	$R^2(\%)$
-0.04	-0.27	0.02	1.27	5.09	8.91

A15. Implied cost of capital

Li et al. (2013) find that the aggregate implied cost of capital (ICC) can be a strong time series predictor of future market return due to the advantage that it is estimated from theoretically justifiable discounted valuation model which takes into account future growth opportunities. Hence, we explore whether ESG can predict future market return through its influence on aggregate ICC. First, we compute ICC which is defined as the discount rate that equates the stock's current price to the present value of expected future cash flows for each stock-month. We follow the approach of Hou et al. (2012) as it adopts regression-based earnings forecasts to alleviate biases in analyst forecasts. Then, we take the value-weighted average of individual stocks' ICCs as the aggregate ICC. Since estimation errors in stock-level ICCs can be reduced by averaging individual stocks' ICCs, the aggregate ICC is likely to be less noisy than stock-level ICCs.

Table A15 reports the regression slope, Newey-West t-value, and monthly $R^2(\%)$ of predicting future aggregate ICC with the composite ESG index. We find that the composite ESG index negatively predicts future aggregate ICC in one month, with a significant t-value of -2.31 and a monthly $R^2(\%)$ of 3.86. We also investigate the one-year horizon forecasting performance of ESG on aggregate ICC, and find that a one-standard deviation increase in the composite ESG index leads to a 0.21% decrease in future aggregate ICC, with a highly significant t-statistic of -3.19 and an in-sample R^2 of 4.79%. Overall, a higher level of composite ESG index indicates a lower level of aggregate ICC in both short and long horizons, suggesting the presence of a discount rate mechanism in driving the market return predictability of ESG.

Table A15: Predicting aggregate implied cost of capital with composite ESG index

This table reports the regression of future aggregate implied cost of capital (ICC) on composite ESG index constructed by aggregating information from individual ESG predictors based on the *PLS* method. The composite ESG index covers all three ESG categories. We compute ICC for each stock-month following the approach of Hou et al. (2012). The aggregate ICC is the value-weighted average of individual stocks' ICCs. We consider aggregate ICC over one-month (1M) and one-year (1Y) horizons. Newey-West t-values are reported.

1M			1Y		
β	t-value	$R^2(\%)$	β	t-value	$R^2(\%)$
-0.02	-2.31	3.86	-0.21	-3.19	4.79

A16: ESG-concern shocks

Pastor et al. (2021) argue that green assets can have higher realized returns than brown assets when concerns about climate change increase unexpectedly, making investors' and customers' tastes shift unexpectedly in the green direction. Hence, we further test whether the interaction term between the composite ESG index (ESG_{t-1}) and unexpected change in aggregate ESG concerns (ΔC_t and ΔC_{t-1}, computed as the prediction error from a first-order autoregressive model applied to aggregate mentioning of risk incidents related to ESG events) can forecast market return. Moreover, we construct two variables, "ESG flows" and "ESG assets", to investigate the effects of ESG investing. "ESG flows" is used as a proxy for shifts in investors' ESG demands and is constructed based on flows into sustainable funds. "ESG assets" is a proxy for the level of investors' ESG tastes and is constructed based on sustainable funds' lagged total assets (AUM). We find that a higher level of investors' ESG tastes leads to lower future market return. This is consistent with the theoretical inference in Pastor et al. (2021) that the equity market premium depends on the average of investors' ESG tastes and the overall greenness of the market portfolio, and that stronger ESG tastes could reduce the equity market premium when the market is net green.

We also add earnings shocks as controls. Specifically, we include two measures of earnings news, "Earnings announcement returns" and "Δ Earnings forecasts", following Pastor et al. (2022). Additionally, we include some commonly used market return predictors such as the dividend yield (DP), the difference in yields between BAA- and AAA-rated corporate bonds (DEF), the difference in yields between long-term and short-term Treasury bonds (TMS), and the detrended risk-free rate ($RREL$). In Panel A of Table A16, we find the market-level composite ESG index (ESG_{t-1}) can still predict market return with a positive sign after controlling the two interaction terms ($ESG_{t-1} \times \Delta C_t$ and $ESG_{t-1} \times \Delta C_{t-1}$), with significant t-statistics of 2.44 and 2.50, respectively. In Panel B, we control unexpected change in climate concern constructed based on the MCCC index from Ardia et al. (2023), and observe similar patterns as in Panel A. In general, the results of Table A16 indicate that the forecasting performance of the composite ESG index on the aggregate market is not fully driven by unexpected change in ESG or climate concerns.

Table A16: Controlling for ESG-concern shocks

This table shows results of regressions in which the dependent variable is market excess return in month t+1, ESG_t is the composite ESG index in month t, constructed by aggregating information from individual ESG predictors based on the *PLS* method, $\triangle C_t$ in Panel A is month t's unexpected change in aggregate ESG concerns, computed as the prediction error from a first-order autoregressive model applied to aggregate mentions of risk incidents related to ESG events, $\triangle C_t$ in Panel B is month t's unexpected change in aggregate climate concerns based on the MCCC index from Ardia et al. (2023). The two earnings news measures, "Earnings announcement returns" and "$\triangle$ Earnings forecasts," follow Pastor et al. (2022). *DP* is the dividend yield; *DFY* is the difference in yields between BAA- and AAA-rated corporate bonds; *TMS* is the dfference in yields between long-term and short-term Treasury bonds; and *RREL* is the detrended risk-free rate.They correspond to the quarter that contains the given month. Newey-West t-values are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
		Panel A: ESG concern			Panel B: Climate concern	
ESG_{t-1}	0.42	0.54	0.39	0.48	0.72	0.78
	(2.05)	(2.44)	(2.50)	(2.10)	(2.49)	(3.89)
$ESG_{t-1} \times \triangle C_t$		-0.06	-0.25		-0.21	-0.31
		(-0.27)	(-1.13)		(-0.81)	(-1.36)
$ESG_{t-1} \times \triangle C_{t-1}$		-0.25	-0.40		-0.11	-0.25
		(-2.05)	(-2.68)		(-0.51)	(-1.23)
ESG flows		0.64	0.92		0.36	0.47
		(2.20)	(2.14)		(1.56)	(1.25)
ESG assets		-0.74	-1.26		-0.59	-0.91
		(-3.00)	(-2.11)		(-2.49)	(-1.73)
Earnings announcement returns		-0.32	-0.07		-0.33	-0.24
		(-0.88)	(-0.22)		(-0.85)	(-0.73)
$\triangle$ Earnings forecasts		0.09	0.17		0.29	0.32
		(0.35)	(0.55)		(0.92)	(1.14)
DP			1.98			1.52
			(4.52)			(4.90)
DFY			-1.01			-0.87
			(-2.43)			(-2.23)
TMS			-0.64			-0.45
			(-1.44)			(-1.03)
RREL			0.74			0.34
			(2.53)			(1.59)
$R^2(\%)$	1.72	5.33	26.62	3.00	7.34	25.01

To bridge the gap between structural theory and practical forecasting, we consider a further revised empirical design, integrating the dynamic considerations on ESG demand shock in Avramov et al. (2024). To incorporate the mechanism of demand shocks over time, the time series predictive regression can be modeled as

$$r_{m,t} = \alpha + \beta_1 ESG_{t-1} + \beta_2 ESG_{t-1} * \Delta C_t + \beta_3 ESG_{t-1} * \Delta C_{t-1} + \varepsilon_t$$

where C_t and ΔC_t proxy for aggregate ESG concern and ESG concern shock, respectively. Consequently, the conditional coefficient on market-level composite ESG index is time-varying and is denoted as $\beta_1 + \beta_2 \Delta C_t + \beta_3 \Delta C_{t-1}$. We plot this conditional coefficient as well as the time series trend of both C_t and ΔC_t in Figure A16.2 and Figure A16.1. This approach effectively "embeds" the preference-shock mechanism of dynamic equilibrium models into an implementable forecast exercise, allowing us to trace how shifts in ESG demand translate into return predictability over time.

Figure A16.1: Time series of aggregate ESG concerns and ESG-concern shocks

Panel A plots the time series of aggregate ESG concerns C_t, where C_t is aggregate mentions of risk incidents related to ESG events in month t. Panel B plots the time series of ESG-concern shocks $\triangle C_t$, where $\triangle C_t$ is month t's unexpected change in aggregate ESG concerns, computed as the prediction error from a first-order autoregressive model applied to C_t. Both series are standardized.

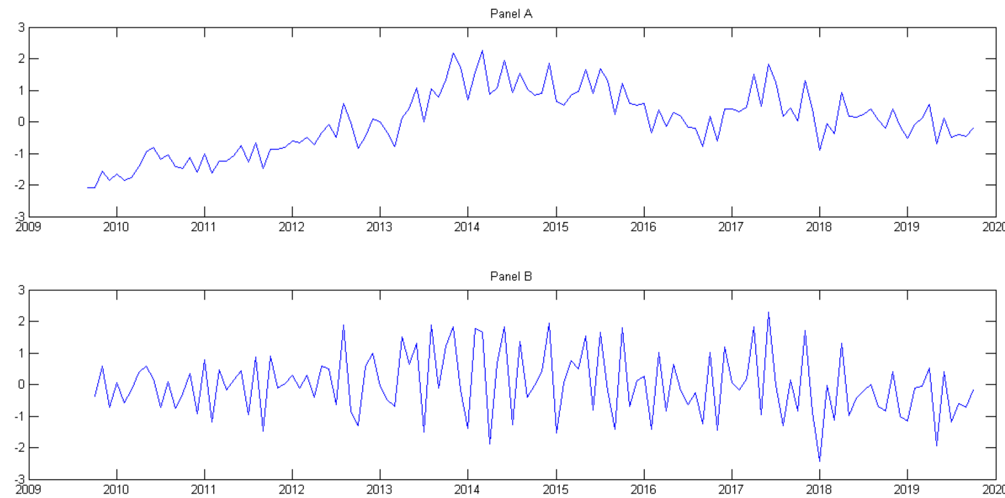
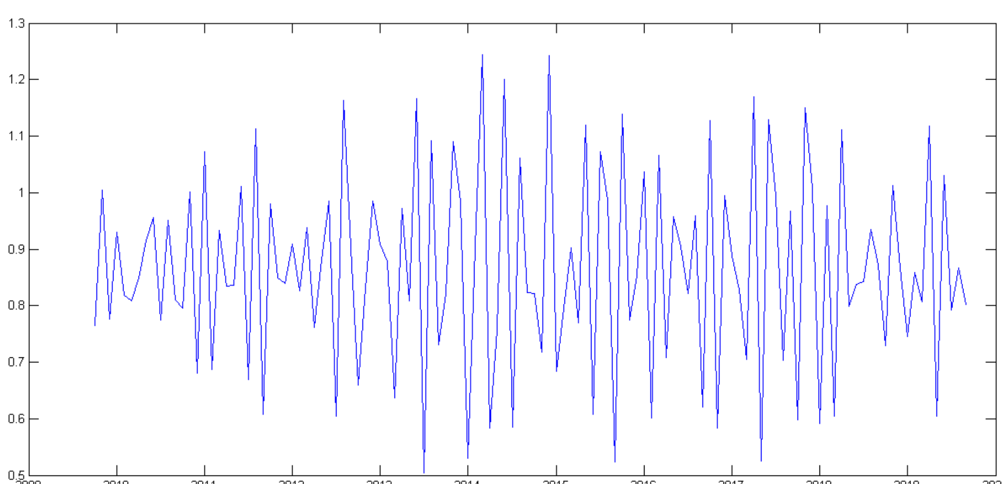


Figure A16.2: Time series of conditional coefficient on the composite ESG index in predictive regression

This figure plots the time series of standardized conditional coefficient $\beta_1 + \beta_2 \Delta C_t + \beta_3 \Delta C_{t-1}$ in predictive regression $r_{m,t} = \alpha + \beta_1 ESG_{t-1} + \beta_2 ESG_{t-1} * \Delta C_t + \beta_3 ESG_{t-1} * \Delta C_{t-1} + \varepsilon_t$, where ESG_t and ΔC_t proxy for the composite ESG index and ESG concern shock in month t, respectively.



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